

SPOTIFY ATTRIBUTES REGRESSION PROJECT

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Project Objective and Overview

The objective of this project is to predict the **msPlayed** (playtime in milliseconds) of songs on **Spotify** based on various song attributes. These attributes include both **continuous** variables such as **danceability**, **energy**, **loudness**, and **tempo**, as well as **categorical** features like **genre** and **artistName**.

The project's core goal is to understand how different musical attributes influence the total playtime of songs and build a regression model to predict future playtime. The dataset includes a variety of song characteristics that provide insights into musical features, which can be useful for music industry professionals and data scientists alike.

By the end of this project, the following objectives will be achieved: - Build a robust **regression model** to predict **msPlayed**. - Understand the significance of various musical features in predicting playtime. - Clean and preprocess the data, handling missing values, duplicates, and categorical features. - Perform **Exploratory Data Analysis (EDA)** to visualize trends and patterns in the data.

Focus of the Project:

- **Primary Application: Music Playtime Prediction**
 - Predicting the playtime (**msPlayed**) based on the attributes of the song.
- **Core Model: Regression Model (Multiple Linear Regression / Polynomial Regression)**
 - Using regression analysis to model the relationship between song attributes and playtime.

Phase-Wise Project Flow

Phase 1: Data Preprocessing & Basic Data Understanding

1. **Data Loading and Initial Exploration**
 - Loading the Spotify Song Attributes dataset and inspecting its structure.
2. **Data Cleaning and Type Modification**
 - Converting columns into appropriate formats and removing redundant or irrelevant columns.
3. **Handling Missing Values and Checking for Duplicates**

- Ensuring no missing values or duplicate records exist.

4. Outlier Detection and Handling

- Identifying and addressing any extreme outliers in key features.

5. Feature Scaling

- Standardizing and normalizing continuous features, making them suitable for regression modeling.
-

Phase 2: Exploratory Data Analysis (EDA)

1. Visualizing Distribution of Attributes

- Visualizing how each feature, especially continuous variables like `danceability`, `energy`, and `msPlayed`, is distributed.

2. Exploring Relationships Between Features

- Using scatter plots, correlation matrices, and other visual tools to explore relationships between the features and `msPlayed`.
-

Phase 3: Feature Engineering & Extraction

1. Handling Categorical Data

- Converting categorical variables like `genre` and `artistName` into factors, and preparing them for model fitting.

2. Creating New Features

- Deriving new features from the existing ones to enhance the predictive power of the model.
-

Phase 4: Model Building

1. Model Selection (Linear/Multiple Regression)

- Selecting a suitable regression model to predict `msPlayed`.

2. Model Evaluation

- Evaluating the model performance using metrics such as R-squared, RMSE, and residual plots.
-

Phase 5: Post-Modeling Analysis

1. Model Refinement

- Making improvements to the model based on diagnostic tests and evaluation metrics.
-

Phase 6: Conclusion and Future Enhancements

1. Summarizing Findings

- Discussing the effectiveness of the regression model and the insights gained.

2. Future Work

- Suggesting improvements, such as trying more complex models (e.g., Random Forest, Gradient Boosting), or exploring additional features for better predictions.

1. Data Collection and Pre-Processing

1.1 Load the Necessary Libraries & Dataset

```
# Load necessary libraries
library(dplyr) # For data manipulation

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##   filter, lag

## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union

library(ggplot2) # Optional, for visualization if needed

# Load the Spotify attribute dataset
data <- read.csv("Spotify_Song_Attributes.csv")
# Create a copy of the spotify attribute dataset
spotify_data <- data
# View the first few rows to understand the structure
head(spotify_data)

##
##                                     trackName
## 1                                     "Honest"
## 2 "In The Hall Of The Mountain King" from Peer Gynt Suite N°1, Op. 46
## 3                                     #BrooklynBloodPop!
## 4                                     $10
## 5                                     (I Just) Died In Your Arms
## 6                                     (L)only Child
##           artistName msPlayed           genre danceability energy key
## 1         Nico Collins   191772           genre danceability energy key
## 2 London Symphony Orchestra 1806234 british orchestra    0.475 0.130 7
## 3              SyKo    145610         glitchcore    0.691 0.814 1
```

```

## 4          Good Morning      25058 experimental pop      0.624 0.596 4
## 5          Cutting Crew    5504949      album rock      0.625 0.726 11
## 6          salem ilese    2237969      alt z      0.645 0.611 8
##    loudness mode speechiness acoustictness instrumentalness liveness valence
## 1    -4.939    0      0.2120      0.0162      0.00e+00 0.2570 0.577
## 2   -17.719    1      0.0510      0.9160      9.56e-01 0.1010 0.122
## 3    -3.788    0      0.1170      0.0164      0.00e+00 0.3660 0.509
## 4    -9.804    1      0.0314      0.4750      2.03e-01 0.1190 0.896
## 5   -11.402    0      0.0444      0.0158      1.69e-04 0.0625 0.507
## 6    -5.925    0      0.1370      0.2900      2.05e-05 0.2370 0.645
##      tempo      type      id
## 1 162.139 audio_features 7dTxqsaFGHOXwtzHINjfHv
## 2 112.241 audio_features 14Qcrx6Dfjvcj0H8oV8oUW
## 3 132.012 audio_features 7K9Z3yFNNLv5kwTjQYGjnu
## 4 120.969 audio_features 3koAwrm1R00TGMeQJ3qt9J
## 5 124.945 audio_features 4ByEF0BuLXpCqv01kw8Wdm
## 6 157.475 audio_features 22lJaG2yxlSjIwdUIddcFk
##      uri
## 1 spotify:track:7dTxqsaFGHOXwtzHINjfHv
## 2 spotify:track:14Qcrx6Dfjvcj0H8oV8oUW
## 3 spotify:track:7K9Z3yFNNLv5kwTjQYGjnu
## 4 spotify:track:3koAwrm1R00TGMeQJ3qt9J
## 5 spotify:track:4ByEF0BuLXpCqv01kw8Wdm
## 6 spotify:track:22lJaG2yxlSjIwdUIddcFk
##      track_href
## 1 https://api.spotify.com/v1/tracks/7dTxqsaFGHOXwtzHINjfHv
## 2 https://api.spotify.com/v1/tracks/14Qcrx6Dfjvcj0H8oV8oUW
## 3 https://api.spotify.com/v1/tracks/7K9Z3yFNNLv5kwTjQYGjnu
## 4 https://api.spotify.com/v1/tracks/3koAwrm1R00TGMeQJ3qt9J
## 5 https://api.spotify.com/v1/tracks/4ByEF0BuLXpCqv01kw8Wdm
## 6 https://api.spotify.com/v1/tracks/22lJaG2yxlSjIwdUIddcFk
##      analysis_url duration_ms
## 1 https://api.spotify.com/v1/audio-analysis/7dTxqsaFGHOXwtzHINjfHv      191948
## 2 https://api.spotify.com/v1/audio-analysis/14Qcrx6Dfjvcj0H8oV8oUW      150827
## 3 https://api.spotify.com/v1/audio-analysis/7K9Z3yFNNLv5kwTjQYGjnu      145611
## 4 https://api.spotify.com/v1/audio-analysis/3koAwrm1R00TGMeQJ3qt9J      89509
## 5 https://api.spotify.com/v1/audio-analysis/4ByEF0BuLXpCqv01kw8Wdm      280400
## 6 https://api.spotify.com/v1/audio-analysis/22lJaG2yxlSjIwdUIddcFk      144468
##      time_signature
## 1      4
## 2      4
## 3      4
## 4      4
## 5      4
## 6      3

```

Inference:

The dataset is successfully loaded into R, and a copy (`spotify_data`) is created to preserve the original data. We can now inspect the first few rows to understand its structure.

1.2 View Dataset Structure

```
# View the structure of the data
str(spotify_data)
```

```
## 'data.frame':    10080 obs. of  22 variables:
##  $ trackName      : chr  "\"Honest\"" "\"In The Hall Of The Mountain King\"" from Peer Gynt Suite N°
##  $ artistName     : chr  "Nico Collins" "London Symphony Orchestra" "SyKo" "Good Morning" ...
##  $ msPlayed       : int  191772 1806234 145610 25058 5504949 2237969 441335 70589 120005 107407 ...
##  $ genre          : chr  "" "british orchestra" "glitchcore" "experimental pop" ...
##  $ danceability    : num  0.476 0.475 0.691 0.624 0.625 0.645 0.663 NA 0.792 0.759 ...
##  $ energy          : num  0.799 0.13 0.814 0.596 0.726 0.611 0.904 NA 0.511 0.699 ...
##  $ key            : num  4 7 1 4 11 8 7 NA 2 0 ...
##  $ loudness       : num  -4.94 -17.72 -3.79 -9.8 -11.4 ...
##  $ mode           : num  0 1 0 1 0 0 1 NA 1 0 ...
##  $ speechiness    : num  0.212 0.051 0.117 0.0314 0.0444 0.137 0.0857 NA 0.0409 0.0307 ...
##  $ acousticness   : num  0.0162 0.916 0.0164 0.475 0.0158 0.29 0.000708 NA 0.124 0.202 ...
##  $ instrumentalness: num  0.00 9.56e-01 0.00 2.03e-01 1.69e-04 2.05e-05 2.89e-01 NA 9.04e-05 1.31e-0
##  $ liveness       : num  0.257 0.101 0.366 0.119 0.0625 0.237 0.341 NA 0.14 0.443 ...
##  $ valence        : num  0.577 0.122 0.509 0.896 0.507 0.645 0.675 NA 0.111 0.907 ...
##  $ tempo          : num  162 112 132 121 125 ...
##  $ type           : chr  "audio_features" "audio_features" "audio_features" "audio_features" ...
##  $ id            : chr  "7dTxqsaFGHOXwtzHINjfHv" "14Qcrx6DfjvcjOH8oV8oUW" "7K9Z3yFNNLv5kwTjQYGjnu"
##  $ uri           : chr  "spotify:track:7dTxqsaFGHOXwtzHINjfHv" "spotify:track:14Qcrx6DfjvcjOH8oV8oUW"
##  $ track_href     : chr  "https://api.spotify.com/v1/tracks/7dTxqsaFGHOXwtzHINjfHv" "https://api.sp
##  $ analysis_url   : chr  "https://api.spotify.com/v1/audio-analysis/7dTxqsaFGHOXwtzHINjfHv" "https:
##  $ duration_ms    : num  191948 150827 145611 89509 280400 ...
##  $ time_signature : num  4 4 4 4 4 3 4 NA 4 4 ...
```

Inference:

The `str()` function provides a quick look at the internal structure of the dataset. We can check the data types (e.g., numeric, factor) of each column, which helps in deciding how to clean or transform the data.

1.3 Summary of Each Column

```
# View a summary of each column (e.g., min, max, mean, etc.)
summary(spotify_data)
```

```
##   trackName      artistName      msPlayed      genre
## Length:10080    Length:10080    Min.   :      0    Length:10080
## Class :character Class :character 1st Qu.: 136780    Class :character
## Mode  :character Mode  :character Median : 266288    Mode  :character
##                                     Mean  : 1519657
##                                     3rd Qu.: 1186307
##                                     Max.   :158367130
##
##   danceability    energy      key      loudness
## Min.   :0.0000    Min.   :0.0011 Min.   : 0.000 Min.   : -42.044
```

```
## 1st Qu.:0.5090 1st Qu.:0.4030 1st Qu.: 2.000 1st Qu.: -10.189
## Median :0.6230 Median :0.5890 Median : 5.000 Median : -7.218
## Mean :0.6025 Mean :0.5635 Mean : 5.242 Mean : -8.685
## 3rd Qu.:0.7140 3rd Qu.:0.7510 3rd Qu.: 8.000 3rd Qu.: -5.336
## Max. :0.9760 Max. :0.9990 Max. :11.000 Max. : 3.010
## NA's :550 NA's :550 NA's :550 NA's :550
## mode speechiness acousticness instrumentalness
## Min. :0.0000 Min. :0.0000 Min. :0.0000 Min. :0.0000
## 1st Qu.:0.0000 1st Qu.:0.0361 1st Qu.:0.0538 1st Qu.:0.0000
## Median :1.0000 Median :0.0479 Median :0.2450 Median :0.0000
## Mean :0.6124 Mean :0.0785 Mean :0.3629 Mean :0.1532
## 3rd Qu.:1.0000 3rd Qu.:0.0819 3rd Qu.:0.6680 3rd Qu.:0.0276
## Max. :1.0000 Max. :0.9660 Max. :0.9960 Max. :0.9930
## NA's :550 NA's :550 NA's :550 NA's :550
## liveness valence tempo type
## Min. :0.0249 Min. :0.0000 Min. : 0.00 Length:10080
## 1st Qu.:0.0962 1st Qu.:0.2370 1st Qu.: 97.57 Class :character
## Median :0.1190 Median :0.4090 Median :119.82 Mode :character
## Mean :0.1746 Mean :0.4341 Mean :119.37
## 3rd Qu.:0.2090 3rd Qu.:0.6140 3rd Qu.:139.78
## Max. :0.9640 Max. :0.9860 Max. :236.20
## NA's :550 NA's :550 NA's :550
## id uri track_href analysis_url
## Length:10080 Length:10080 Length:10080 Length:10080
## Class :character Class :character Class :character Class :character
## Mode :character Mode :character Mode :character Mode :character
##
##
##
## duration_ms time_signature
## Min. : 10027 Min. :0.000
## 1st Qu.: 161697 1st Qu.:4.000
## Median : 194286 Median :4.000
## Mean : 202931 Mean :3.917
## 3rd Qu.: 229526 3rd Qu.:4.000
## Max. :4581483 Max. :5.000
## NA's :550 NA's :550
```

Inference:

The summary statistics allow us to understand the distribution of each feature, including mean, min, max, and standard deviation. This is crucial for identifying outliers and deciding which variables require special treatment.

1.4 Handling Missing Values

```
# Check for missing values in each column
colSums(is.na(spotify_data))
```

```
## trackName artistName msPlayed genre
```

```
##           0           0           0           0
##  danceability      energy      key      loudness
##           550          550          550          550
##           mode      speechiness  acousticness  instrumentalness
##           550          550          550          550
##      liveness      valence      tempo      type
##           550          550          550          0
##           id      uri      track_href      analysis_url
##           0           0           0           0
##      duration_ms  time_signature
##           550          550
```

We can see:

1. **Columns with Zero Missing Values:** Columns like `trackName`, `artistName`, `msPlayed`, `genre`, `id`, `uri`, `track_href`, `analysis_url`, and `type` have no missing values, ensuring they are complete for analysis.
2. **Columns with 550 Missing Values:** Columns such as `danceability`, `energy`, `key`, `loudness`, `mode`, `speechiness`, `acousticness`, `instrumentalness`, `liveness`, `valence`, `tempo`, `duration_ms`, and `time_signature` have significant missing values (550). This indicates a need to address these missing entries to ensure reliable analysis.

1.4.1 Remove Missing Values

```
# Option 1: Remove rows with missing values (if they are few)
spotify_data <- na.omit(spotify_data)
```

Inference:

Using `na.omit()` removes rows with missing data, leaving us with only complete observations. This is necessary for regression models, which cannot handle missing values.

1.4.2 Check Missing Values After Removal

```
# Check for missing values in each column after applying na.omit function
colSums(is.na(spotify_data))
```

```
##      trackName      artistName      msPlayed      genre
##           0           0           0           0
##  danceability      energy      key      loudness
##           0           0           0           0
##           mode      speechiness  acousticness  instrumentalness
##           0           0           0           0
##      liveness      valence      tempo      type
##           0           0           0           0
##           id      uri      track_href      analysis_url
##           0           0           0           0
##      duration_ms  time_signature
##           0           0
```

All values being zero in the output confirms that no missing data remains in the dataset. This clean dataset now contains only complete rows, ideal for accurate and consistent analysis.

Just check missing values removed from structure data or not.

```
str(spotify_data)
```

```
## 'data.frame':    9530 obs. of  22 variables:
## $ trackName      : chr  "\"Honest\"" "\"In The Hall Of The Mountain King\"" from Peer Gynt Suite N°
## $ artistName     : chr  "Nico Collins" "London Symphony Orchestra" "SyKo" "Good Morning" ...
## $ msPlayed       : int  191772 1806234 145610 25058 5504949 2237969 441335 120005 107407 21354 ...
## $ genre          : chr  "" "british orchestra" "glitchcore" "experimental pop" ...
## $ danceability   : num  0.476 0.475 0.691 0.624 0.625 0.645 0.663 0.792 0.759 0.742 ...
## $ energy         : num  0.799 0.13 0.814 0.596 0.726 0.611 0.904 0.511 0.699 0.675 ...
## $ key            : num  4 7 1 4 11 8 7 2 0 8 ...
## $ loudness       : num  -4.94 -17.72 -3.79 -9.8 -11.4 ...
## $ mode           : num  0 1 0 1 0 0 1 1 0 1 ...
## $ speechiness    : num  0.212 0.051 0.117 0.0314 0.0444 0.137 0.0857 0.0409 0.0307 0.0907 ...
## $ acousticness   : num  0.0162 0.916 0.0164 0.475 0.0158 0.29 0.000708 0.124 0.202 0.139 ...
## $ instrumentalness: num  0.00 9.56e-01 0.00 2.03e-01 1.69e-04 2.05e-05 2.89e-01 9.04e-05 1.31e-04 0
## $ liveness       : num  0.257 0.101 0.366 0.119 0.0625 0.237 0.341 0.14 0.443 0.167 ...
## $ valence        : num  0.577 0.122 0.509 0.896 0.507 0.645 0.675 0.111 0.907 0.679 ...
## $ tempo          : num  162 112 132 121 125 ...
## $ type           : chr  "audio_features" "audio_features" "audio_features" ...
## $ id             : chr  "7dTxqsaFGHOXwtzHINjfHv" "14Qcrx6Dfjvcj0H8oV8oUW" "7K9Z3yFNNLv5kwTjQYGjnu"
## $ uri            : chr  "spotify:track:7dTxqsaFGHOXwtzHINjfHv" "spotify:track:14Qcrx6Dfjvcj0H8oV8oUW"
## $ track_href     : chr  "https://api.spotify.com/v1/tracks/7dTxqsaFGHOXwtzHINjfHv" "https://api.sp
## $ analysis_url   : chr  "https://api.spotify.com/v1/audio-analysis/7dTxqsaFGHOXwtzHINjfHv" "https:
## $ duration_ms    : num  191948 150827 145611 89509 280400 ...
## $ time_signature : num  4 4 4 4 4 3 4 4 4 4 ...
## - attr(*, "na.action")= 'omit' Named int [1:550] 8 48 77 78 109 123 125 129 132 142 ...
## ..- attr(*, "names")= chr [1:550] "8" "48" "77" "78" ...
```

1.5 Remove Unwanted Columns

```
# Load dplyr library
library(dplyr)

# Remove `trackName` along with other unnecessary columns
spotify_data <- spotify_data %>% select(-id, -uri, -track_href, -analysis_url, -trackName, -type)
```

Statistical Reasoning for Dropping Variables:

- **id, uri, track_href, analysis_url, trackName, type:** These columns do not contribute to predicting msPlayed. They are either unique identifiers or non-informative for the analysis.

```
# Check the specified columns have been removed or not
str(spotify_data)
```



```
## 'data.frame':    9530 obs. of  16 variables:
## $ artistName      : chr  "Nico Collins" "London Symphony Orchestra" "SyKo" "Good Morning" ...
## $ msPlayed        : int  191772 1806234 145610 25058 5504949 2237969 441335 120005 107407 21354 ...
## $ genre           : chr  "" "british orchestra" "glitchcore" "experimental pop" ...
## $ danceability     : num  0.476 0.475 0.691 0.624 0.625 0.645 0.663 0.792 0.759 0.742 ...
## $ energy           : num  0.799 0.13 0.814 0.596 0.726 0.611 0.904 0.511 0.699 0.675 ...
## $ key              : num  4 7 1 4 11 8 7 2 0 8 ...
## $ loudness         : num  -4.94 -17.72 -3.79 -9.8 -11.4 ...
## $ mode             : num  0 1 0 1 0 0 1 1 0 1 ...
## $ speechiness      : num  0.212 0.051 0.117 0.0314 0.0444 0.137 0.0857 0.0409 0.0307 0.0907 ...
## $ acousticness     : num  0.0162 0.916 0.0164 0.475 0.0158 0.29 0.000708 0.124 0.202 0.139 ...
## $ instrumentalness : num  0.00 9.56e-01 0.00 2.03e-01 1.69e-04 2.05e-05 2.89e-01 9.04e-05 1.31e-04 0 ...
## $ liveness         : num  0.257 0.101 0.366 0.119 0.0625 0.237 0.341 0.14 0.443 0.167 ...
## $ valence          : num  0.577 0.122 0.509 0.896 0.507 0.645 0.675 0.111 0.907 0.679 ...
## $ tempo            : num  162 112 132 121 125 ...
## $ duration_ms      : num  191948 150827 145611 89509 280400 ...
## $ time_signature   : num  4 4 4 4 4 3 4 4 4 4 ...
## - attr(*, "na.action")= 'omit' Named int [1:550] 8 48 77 78 109 123 125 129 132 142 ...
## ..- attr(*, "names")= chr [1:550] "8" "48" "77" "78" ...
```

1.6 Data Cleaning

1.6.1 Check Whitespace in artistName Column

```
# Check for leading or trailing whitespace
whitespace_issues <- spotify_data$artistName[grepl("^\\s|\\s$", spotify_data$artistName)]

# Display entries with whitespace issues
print(whitespace_issues)
```

```
## character(0)
```

Inference:

Whitespace in `artistName` can cause inconsistencies, so it is necessary to clean these entries.

1.6.2 Identify Special Characters in artistName

```
# Identify special characters in artist names
special_characters <- spotify_data$artistName[grepl("[^a-zA-Z0-9\\s]", spotify_data$artistName)]

# Display total number of entries with special characters and the first 25 entries
cat("Total number of ntries with Special Characters:", length(special_characters), "\n")
```

```
## Total number of ntries with Special Characters: 6030
```

```
head(special_characters, 25)
```

```
## [1] "Nico Collins" "London Symphony Orchestra"
## [3] "Good Morning" "Cutting Crew"
## [5] "salem ilese" "Eren Cannata"
## [7] "$uicideboy$" "Britney Spears"
## [9] "Sidhu Moose Wala" "colours in the dark"
## [11] "Dan + Shay" "mj apanay"
## [13] "Chris James" "Zach Hood"
## [15] "Josh Golden" "Shiloh Dynasty"
## [17] "Jeremy Zucker" "Thomas Newman"
## [19] "Bo Burnham" "Linkin Park"
## [21] "Marco Luka" "Sleepy Hallow"
## [23] "Comfort Club" "Johannes Brahms"
## [25] "Seattle Symphony Orchestra"
```

Inference:

Special characters in `artistName` can cause inconsistencies when grouping artists. Identifying these characters helps ensure that they are cleaned properly.

1.6.3 Identifying Duplicated Artist Names

```
# Identify duplicated artist names after cleaning
duplicate_artists <- spotify_data$artistName[duplicated(spotify_data$artistName)]

# Display total number of duplicates and the first 10 duplicate entries
cat("Total number of duplicates:", length(duplicate_artists), "\n")
```

```
## Total number of duplicates: 7343
```

```
head(duplicate_artists, 10)
```

```
## [1] "glaive" "Johannes Brahms"
## [3] "Lauv" "Chris James"
## [5] "Ed Sheeran" "Ed Sheeran"
## [7] "blackbear" "blackbear"
## [9] "High School Musical Cast" "KUTE"
```

Inference:

This output shows the total number of duplicate artist names and the first 10 duplicates, helping confirm that duplicate names are properly handled.

1.6.4 Replace Special Characters

```
# Replace special characters like $ with s (only if necessary)
spotify_data$artistName <- gsub("\\$", "s", spotify_data$artistName)
```

Inference:

Replacing special characters ensures that `artistName` values are consistent, removing unwanted characters that may interfere with analysis.

1.6.5 Convert Artist Names to Lowercase

```
# Convert artistName to lowercase
spotify_data$artistName <- tolower(spotify_data$artistName)
```

Inference:

Lowercasing ensures that variations in capitalization are removed, making artist names uniform for analysis.

1.6.6 Removing Identical Rows

```
# Removing rows that are identical across all columns
spotify_data <- distinct(spotify_data)
```

Inference:

Removing identical rows ensures that only unique entries are retained, reducing redundancy in the dataset.

1.6.7 Group Rare Artists into “Other”

```
# Group artists with fewer than the threshold of entries into "Other"
threshold <- 5
artist_counts <- table(spotify_data$artistName)
rare_artists <- names(artist_counts[artist_counts < threshold])
spotify_data$artistName <- ifelse(spotify_data$artistName %in% rare_artists, "Other", spotify_data$artistName)
```

Inference:

Grouping rare artists under the “Other” category reduces the number of unique categories, simplifying the model and making it easier to interpret.

1.6.8 Convert Artist Names to Factor

```
# Convert artistName to a factor
spotify_data$artistName <- as.factor(spotify_data$artistName)
```

Inference:

Converting `artistName` to a factor ensures that it is correctly handled as a categorical variable in regression modeling.

1.6.9 Let's Clean the Genre Column

```
# Checking the genre data  
head(spotify_data$genre)
```

```
## [1] "" "british orchestra" "glitchcore"  
## [4] "experimental pop" "album rock" "alt z"
```

```
head(unique(spotify_data$genre), 25)
```

```
## [1] "" "british orchestra"  
## [3] "glitchcore" "experimental pop"  
## [5] "album rock" "alt z"  
## [7] "guitar case" "cloud rap"  
## [9] "dance pop" "desi hip hop"  
## [11] "lo-fi sleep" "contemporary country"  
## [13] "bedroom r&b" "singer-songwriter pop"  
## [15] "la pop" "lo-fi chill"  
## [17] "orchestral soundtrack" "comic"  
## [19] "alternative metal" "deep underground hip hop"  
## [21] "pop" "brooklyn drill"  
## [23] "classical" "american orchestra"  
## [25] "modern alternative rock"
```

```
# Count missing values  
sum(is.na(spotify_data$genre) | spotify_data$genre == "")
```

```
## [1] 475
```

Output Interpretation: This output helps identify how many `genre` values are missing or empty, guiding further cleaning steps.

```
# Replace empty genre values with "unknown"  
spotify_data$genre[spotify_data$genre == ""] <- "unknown"
```

Inference: Replacing empty genre values with “unknown” ensures that no missing data is mistakenly treated as an empty string.

```
# Convert genre names to lowercase  
spotify_data$genre <- tolower(spotify_data$genre)
```

```
# Display the frequency of genres
genre_counts <- sort(table(spotify_data$genre), decreasing = TRUE)
print(genre_counts)
```

```
##
##          unknown          alt z
##          475          328
##          pop          filmi
##          301          206
##          dance pop          singer-songwriter pop
##          86          82
##          alternative metal          anime lo-fi
##          75          68
##          art pop          drift phonk
##          63          62
##          brostep          modern alternative rock
##          58          56
##          lo-fi study          edm
##          55          50
##          anime          chill pop
##          49          47
##          classical          j-pop
##          46          46
##          cloud rap          la pop
##          44          42
##          modern rock          lo-fi sleep
##          40          37
##          boy band          lo-fi chill
##          36          35
##          baroque pop          german soundtrack
##          34          34
##          modern indie pop          desi hip hop
##          34          33
##          icelandic indie          bedroom pop
##          33          32
##          desi pop          hip hop
##          32          32
##          alternative dance          gen z singer-songwriter
##          31          31
##          anime score          classic bollywood
##          29          29
##          dark r&b          sad lo-fi
##          26          26
##          canadian pop          electropop
##          25          24
##          folk-pop          pov: indie
##          24          24
##          album rock          gym phonk
##          23          23
##          indie pop          alternative rock
##          23          22
##          lo-fi beats          canadian contemporary r&b
##          22          21
```

##	australian pop	detroit hip hop
##	20	20
##	emo rap	glitchcore
##	20	20
##	indie popoptimism	pop rap
##	20	20
##	bedroom soul	shanty
##	19	19
##	atl hip hop	canadian electronic
##	17	17
##	post-teen pop	sad rap
##	16	16
##	british singer-songwriter	hopebeat
##	15	15
##	indietronica	k-pop
##	15	15
##	alabama indie	complextro
##	14	14
##	dfw rap	bedroom r&b
##	14	13
##	canadian hip hop	chillwave
##	13	13
##	downtempo	indie anthem-folk
##	13	13
##	lo-fi jazzhop	pop dance
##	13	13
##	viral pop	acoustic pop
##	13	12
##	aesthetic rap	alternative r&b
##	12	12
##	chicago rap	classic pakistani pop
##	12	12
##	traprun	uk pop
##	12	12
##	alternative hip hop	australian dance
##	11	11
##	bass trap	japanese chillhop
##	11	11
##	pop edm	swedish pop
##	11	11
##	video game music	aggressive phonk
##	11	10
##	ambient folk	bossbeat
##	10	10
##	disco	electro house
##	10	10
##	glitch hop	chill r&b
##	10	9
##	classic rock	easy listening
##	9	9
##	french shoegaze	future bass
##	9	9
##	indie game soundtrack	indie r&b
##	9	9

##	melodic rap	piano rock
##	9	9
##	r&b	afghan pop
##	9	8
##	australian rock	baroque
##	8	8
##	big room	chamber pop
##	8	8
##	contemporary country	hyperpop
##	8	8
##	indie pop rap	lgbtq+ hip hop
##	8	8
##	modern alternative pop	social media pop
##	8	8
##	sped up	ambient pop
##	8	7
##	chill phonk	chillhop
##	7	7
##	chillstep	chutney
##	7	7
##	dutch edm	dutch house
##	7	7
##	eurodance	hollywood
##	7	7
##	metropopolis	neo mellow
##	7	7
##	new french touch	orchestral soundtrack
##	7	7
##	australian hip hop	chanson
##	6	6
##	covertronica	gaming edm
##	6	6
##	gauze pop	indie electropop
##	6	6
##	melodic dubstep	modern bollywood
##	6	6
##	punjabi pop	scandipop
##	6	6
##	alternative pop rock	austindie
##	5	5
##	brazilian edm	british soundtrack
##	5	5
##	conscious hip hop	east coast hip hop
##	5	5
##	grunge	japanese teen pop
##	5	5
##	lo-fi brasileiro	new romantic
##	5	5
##	otacore	pop r&b
##	5	5
##	punjabi hip hop	reggaeton
##	5	5
##	sleep	speedrun
##	5	5

##	super eurobeat	adult standards
##	5	4
##	afrofuturism	ambient guitar
##	4	4
##	ambient worship	antiviral pop
##	4	4
##	arkansas country	aussietronica
##	4	4
##	australian electropop	bhangra
##	4	4
##	black americana	bow pop
##	4	4
##	british soul	broadway
##	4	4
##	brooklyn indie	ccm
##	4	4
##	classic country pop	danish pop
##	4	4
##	deep underground hip hop	denpa-kei
##	4	4
##	electro-pop francais	europop
##	4	4
##	focus beats	glam metal
##	4	4
##	indie rock	indonesian r&b
##	4	4
##	irish singer-songwriter	j-acoustic
##	4	4
##	k-rap	korean r&b
##	4	4
##	la indie	meme
##	4	4
##	nashville singer-songwriter	nyc pop
##	4	4
##	pakistani pop	shimmer pop
##	4	4
##	slap house	soundtrack
##	4	4
##	afrobeats	anime rock
##	3	3
##	australian indie	australian psych
##	3	3
##	bass house	bhajan
##	3	3
##	boy pop	chill house
##	3	3
##	country	dark trap
##	3	3
##	dreamo	dutch pop
##	3	3
##	electra	electronica
##	3	3
##	emo	escape room
##	3	3

##	experimental pop	filter house
##	3	3
##	garage rock	hindi indie
##	3	3
##	hip pop	indian indie
##	3	3
##	indie garage rock	indie rockism
##	3	3
##	instrumental post-rock	irish pop
##	3	3
##	modern indie folk	norwegian pop
##	3	3
##	pixel	pop folk
##	3	3
##	reggae fusion	scorecore
##	3	3
##	show tunes	slowed and reverb
##	3	3
##	solipsynthm	teen pop
##	3	3
##	tempe indie	trip hop
##	3	3
##	viral rap	alaska indie
##	3	2
##	anime phonk	arab electronic
##	2	2
##	australian r&b	barbadian pop
##	2	2
##	bc underground hip hop	belgian dance
##	2	2
##	belgian edm	belgian indie
##	2	2
##	belgian rock	brazilian house
##	2	2
##	british indie rock	british orchestra
##	2	2
##	brooklyn drill	canadian latin
##	2	2
##	candy pop	cantopop
##	2	2
##	cedm	chamber psych
##	2	2
##	channel pop	chicago house
##	2	2
##	chill out	christian alternative rock
##	2	2
##	christian hip hop	classic swedish pop
##	2	2
##	classic uk pop	comic
##	2	2
##	dance rock	dancefloor dnb
##	2	2
##	deep tropical house	epicore
##	2	2

##	eurobeat	french pop
##	2	2
##	g funk	garage rock revival
##	2	2
##	german dance	glam rock
##	2	2
##	gregorian dance	hard rock
##	2	2
##	house	indie folk
##	2	2
##	indiecoustica	indonesian singer-songwriter
##	2	2
##	industrial pop	israeli mediterranean
##	2	2
##	israeli pop	j-poprock
##	2	2
##	j-rock	japanese alternative pop
##	2	2
##	japanese dance pop	japanese dub
##	2	2
##	jazz cover	korean electropop
##	2	2
##	korean pop	latin hip hop
##	2	2
##	leeds indie	lo-fi cover
##	2	2
##	lo-fi indie	mandopop
##	2	2
##	melbourne bounce international	melodic metalcore
##	2	2
##	minneapolis indie	nashville indie
##	2	2
##	neo soul	new jersey indie
##	2	2
##	newfoundland indie	nightcore
##	2	2
##	norwegian house	ohio hip hop
##	2	2
##	permanent wave	pittsburgh rap
##	2	2
##	plugg	stomp and holler
##	2	2
##	stutter house	swedish electropop
##	2	2
##	swiss indie	toronto indie
##	2	2
##	trap	uk dance
##	2	2
##	uk hip hop	vapor twitch
##	2	2
##	weirdcore	a cappella
##	2	1
##	abstract	abstract beats
##	1	1

##	abstract hip hop	acoustic opm
##	1	1
##	alabama rap	alternative americana
##	1	1
##	ambient lo-fi	american modern classical
##	1	1
##	american orchestra	anime latino
##	1	1
##	anime piano	ann arbor indie
##	1	1
##	anthem worship	arab trap
##	1	1
##	argentine ambient	armenian hip hop
##	1	1
##	asian american hip hop	assamese pop
##	1	1
##	atmospheric dnb	austin rock
##	1	1
##	australian alternative pop	australian singer-songwriter
##	1	1
##	ballet class	belgian pop
##	1	1
##	bhojpuri pop	blues
##	1	1
##	blues rock	brazilian bass
##	1	1
##	brighton indie	britcore
##	1	1
##	british alternative rock	british modern classical
##	1	1
##	bubblegum dance	cali rap
##	1	1
##	calming instrumental	canadian celtic
##	1	1
##	canadian old school hip hop	canadian singer-songwriter
##	1	1
##	celtic rock	chennai indie
##	1	1
##	chicago indie	children's folk
##	1	1
##	chill baile	chinese classical performance
##	1	1
##	chinese electropop	chinese idol pop
##	1	1
##	chinese viral pop	chiptune
##	1	1
##	christian lo-fi	christian rock
##	1	1
##	cincinnati indie	cinematic dubstep
##	1	1
##	city pop	classic bhangra
##	1	1
##	classic progressive house	classic soul
##	1	1

##	classic texas country	classical performance
##	1	1
##	cleveland indie	colombian pop
##	1	1
##	compositional ambient	contemporary r&b
##	1	1
##	cumbia	cyberpunk
##	1	1
##	danish electronic	danish electropop
##	1	1
##	dark clubbing	dark plugg
##	1	1
##	dark pop	death metal
##	1	1
##	detroit indie	disco house
##	1	1
##	diva house	dmv rap
##	1	1
##	dutch indie	electro
##	1	1
##	electroclash	english indie rock
##	1	1
##	erhu	estonian electronic
##	1	1
##	ethereal wave	fingerstyle
##	1	1
##	finnish alternative rock	florida drill
##	1	1
##	folktronica	freeform hardcore
##	1	1
##	french hip hop	french indie pop
##	1	1
##	french psychedelic	funk
##	1	1
##	funk carioca	funk metal
##	1	1
##	future rock	g-house
##	1	1
##	gambian hip hop	game mood
##	1	1
##	gangster rap	german pop
##	1	1
##	german pop rock	girl group
##	1	1
##	glitch	guitar case
##	1	1
##	gujarati pop	hands up
##	1	1
##	hard bass	hare krishna
##	1	1
##	hawaiian	hawaiian hip hop
##	1	1
##	hi-nrg	himachali pop
##	1	1

##	hmong pop	hungarian classical performance
##	1	1
##	hypnagogic pop	indian lo-fi
##	1	1
##	indie emo	indie rock italiano
##	1	1
##	indie soul	indie viet
##	1	1
##	indonesian lo-fi pop	instrumental grime
##	1	1
##	instrumental math rock	irish rock
##	1	1
##	italian indie pop	italian library music
##	1	1
##	j-ambient	j-idol
##	1	1
##	j-pop boy group	j-pop girl group
##	1	1
##	japanese alternative rock	japanese old school hip hop
##	1	1
##	japanese piano	japanese vgm
##	1	1
##	jazz rap	josei rap
##	1	1
##	k-pop girl group	kazakh pop
##	1	1
##	latin pop	lilith
##	1	1
##	liquid funk	lithuanian electronic
##	1	1
##	lo-fi latino	lo-fi product
##	1	1
##	lo-fi rap	malaysian pop
##	1	1
##	manitoba indie	melodic drill
##	1	1
##	melodipop	meme rap
##	1	1
##	memphis hip hop	metallic hardcore
##	1	1
##	minimal tech house	modern dream pop
##	1	1
##	modern folk rock	musica indigena latinoamericana
##	1	1
##	musica portuguesa contemporanea	native american
##	1	1
##	neon pop punk	new england americana
##	1	1
##	new wave pop	nightrun
##	1	1
##	noise pop	nordic house
##	1	1
##	nu disco	nuevo folklore mexicano
##	1	1

##	nyc rap	nz hip hop
##	1	1
##	nz pop	odia bhajan
##	1	1
##	odia pop	oxford indie
##	1	1
##	pakistani electronic	pakistani hip hop
##	1	1
##	persian electronic	persian pop
##	1	1
##	phonk brasileiro	pinoy hip hop
##	1	1
##	pluggnb	pop quebecois
##	1	1
##	pop soul	post-grunge
##	1	1
##	rage rap	rap rock
##	1	1
##	romanian pop	russian drain
##	1	1
##	russian drill	russian pop
##	1	1
##	scottish indie	shimmer psych
##	1	1
##	singaporean pop	singaporean singer-songwriter
##	1	1
##	sleaze rock	soul jazz
##	1	1
##	south african pop	swedish singer-songwriter
##	1	1
##	swiss pop	tech house
##	1	1
##	telugu indie	thai indie rock
##	1	1
##	trap queen	turkish edm
##	1	1
##	uk alternative hip hop	uk contemporary r&b
##	1	1
##	ukrainian viral pop	vapor pop
##	1	1
##	virginia indie	vocal trance
##	1	1
##	wave	wonky
##	1	1

Inference: The frequency table provides insights into the distribution of genres, helping identify the most common and rare genres for possible standardization.

```
# Replace empty strings and unknown genres with NA
spotify_data$genre[spotify_data$genre == "" | spotify_data$genre == "unknown"] <- NA
```

```
# Define a mapping for genre standardization
genre_mapping <- c(
```

```

# General categories
"alt z" = "alternative",
"art pop" = "alternative",
"alternative metal" = "alternative rock",
"modern alternative rock" = "alternative rock",
"alternative pop rock" = "alternative rock",
"alternative r&b" = "r&b",
"alternative dance" = "dance",

# Lo-fi variations
"lo-fi sleep" = "lo-fi",
"lo-fi study" = "lo-fi",
"lo-fi chill" = "lo-fi",
"lo-fi beats" = "lo-fi",
"anime lo-fi" = "lo-fi",
"sad lo-fi" = "lo-fi",

# Pop variations
"post-teen pop" = "pop",
"gen z singer-songwriter" = "pop",
"singer-songwriter pop" = "pop",
"viral pop" = "pop",
"bedroom pop" = "pop",
"pop soul" = "pop",
"alt pop" = "pop",

# Hip hop variations
"atl hip hop" = "hip hop",
"traprun" = "trap",
"cloud rap" = "hip hop",
"emo rap" = "rap",
"sad rap" = "rap",
"brooklyn drill" = "drill",
"drift phonk" = "phonk",
"conscious hip hop" = "hip hop",
"canadian hip hop" = "hip hop",
"ohio hip hop" = "hip hop",

# R&B variations
"dark r&b" = "r&b",
"bedroom r&b" = "r&b",
"chill r&b" = "r&b",
"indie r&b" = "r&b",
"pop r&b" = "r&b",
"uk contemporary r&b" = "r&b",

# EDM and Dance variations
"dance pop" = "edm",
"bass house" = "edm",
"chillwave" = "edm",
"future bass" = "edm",
"edm" = "edm",
"house" = "edm",

```

```

"eurodance" = "edm",
"gaming edm" = "edm",

# Classical variations
"baroque" = "classical",
"classical performance" = "classical",
"german soundtrack" = "classical",
"orchestral soundtrack" = "classical",
"baroque pop" = "classical",

# Rock variations
"album rock" = "rock",
"blues rock" = "rock",
"indie rock" = "rock",
"modern rock" = "rock",
"hard rock" = "rock",
"garage rock" = "rock",
"grunge" = "rock",
"alternative rock" = "rock",

# Indie variations
"indie pop" = "indie",
"indie poptimism" = "indie",
"indie folk" = "indie",
"indie electropop" = "indie",
"indie game soundtrack" = "indie",
"indie anthem-folk" = "indie",
"indie garage rock" = "indie",

# Anime and J-Pop
"anime score" = "anime",
"anime rock" = "anime",
"anime phonk" = "anime",
"j-pop" = "japanese pop",
"japanese teen pop" = "japanese pop",
"japanese vgm" = "japanese pop",

# Other Genre Variations
"pov: indie" = "indie",
"ambient guitar" = "ambient",
"ambient pop" = "ambient",
"aesthetic rap" = "rap",
"vapor twitch" = "vaporwave",
"vapor pop" = "vaporwave",
"brooklyn indie" = "indie",
"downtempo" = "ambient",
"chill phonk" = "phonk",
"melodic rap" = "rap",
"neo mellow" = "mellow",
"post-grunge" = "grunge",
"emo" = "rock"

```

)


```
# Standardize genres using the recode function
spotify_data$genre <- recode(spotify_data$genre, !!!genre_mapping)

# Check if the genre column was updated
unique(spotify_data$genre)
```

```
## [1] NA "british orchestra"
## [3] "glitchcore" "experimental pop"
## [5] "rock" "alternative"
## [7] "guitar case" "hip hop"
## [9] "edm" "desi hip hop"
## [11] "lo-fi" "contemporary country"
## [13] "r&b" "pop"
## [15] "la pop" "classical"
## [17] "comic" "alternative rock"
## [19] "deep underground hip hop" "drill"
## [21] "american orchestra" "scandipop"
## [23] "alabama indie" "stomp and holler"
## [25] "anime" "dfw rap"
## [27] "punjabi pop" "folk-pop"
## [29] "acoustic pop" "filmi"
## [31] "japanese pop" "sleep"
## [33] "electronica" "australian pop"
## [35] "danish pop" "rap"
## [37] "boy band" "solipsynthm"
## [39] "ambient" "show tunes"
## [41] "hollywood" "instrumental post-rock"
## [43] "canadian contemporary r&b" "aggressive phonk"
## [45] "hindi indie" "himachali pop"
## [47] "odia bhajan" "desi pop"
## [49] "classic bollywood" "afghan pop"
## [51] "chutney" "metropopolis"
## [53] "shanty" "chill pop"
## [55] "glam rock" "brostep"
## [57] "disco" "channel pop"
## [59] "british singer-songwriter" "melodic drill"
## [61] "easy listening" "indian lo-fi"
## [63] "detroit hip hop" "modern indie pop"
## [65] "australian dance" "hip pop"
## [67] "dutch house" "canadian electronic"
## [69] "video game music" "k-pop"
## [71] "irish pop" "candy pop"
## [73] "indie pop rap" "neo soul"
## [75] "classic pakistani pop" "japanese chillhop"
## [77] "japanese dub" "electra"
## [79] "social media pop" "electro house"
## [81] "bhangra" "afrobeats"
## [83] "gregorian dance" "electropop"
## [85] "lo-fi indie" "lo-fi jazzhop"
## [87] "korean r&b" "ambient folk"
## [89] "europop" "indie"
## [91] "dutch edm" "indian indie"
## [93] "pop edm" "classic rock"
```

## [95]	"glitch hop"	"canadian pop"
## [97]	"icelandic indie"	"complextro"
## [99]	"piano rock"	"lo-fi brasileiro"
## [101]	"dutch pop"	"phonk"
## [103]	"shimmer pop"	"italian indie pop"
## [105]	"lo-fi latino"	"bedroom soul"
## [107]	"dancefloor dnb"	"nordic house"
## [109]	"pakistani pop"	"new french touch"
## [111]	"pop rap"	"vaporwave"
## [113]	"trap"	"dark trap"
## [115]	"big room"	"josei rap"
## [117]	"super eurobeat"	"stutter house"
## [119]	"australian rock"	"uk dance"
## [121]	"minneapolis indie"	"afrofuturism"
## [123]	"britcore"	"french hip hop"
## [125]	"leeds indie"	"minimal tech house"
## [127]	"chill out"	"denpa-kei"
## [129]	"brazilian house"	"hands up"
## [131]	"bass trap"	"nu disco"
## [133]	"chamber pop"	"aussietronica"
## [135]	"mandopop"	"indie rock italiano"
## [137]	"alaska indie"	"estonian electronic"
## [139]	"bossbeat"	"romanian pop"
## [141]	"antiviral pop"	"belgian edm"
## [143]	"irish rock"	"modern alternative pop"
## [145]	"japanese alternative pop"	"rage rap"
## [147]	"nyc pop"	"hyperpop"
## [149]	"instrumental grime"	"russian drain"
## [151]	"broadway"	"singaporean pop"
## [153]	"j-poprock"	"alternative hip hop"
## [155]	"british indie rock"	"turkish edm"
## [157]	"chillhop"	"nightcore"
## [159]	"classic texas country"	"ukrainian viral pop"
## [161]	"abstract beats"	"indonesian r&b"
## [163]	"sped up"	"chicago rap"
## [165]	"instrumental math rock"	"pittsburgh rap"
## [167]	"lo-fi cover"	"colombian pop"
## [169]	"french pop"	"focus beats"
## [171]	"gym phonk"	"nuevo folklore mexicano"
## [173]	"hard bass"	"russian pop"
## [175]	"israeli mediterranean"	"israeli pop"
## [177]	"thai indie rock"	"j-rock"
## [179]	"japanese dance pop"	"chinese viral pop"
## [181]	"japanese alternative rock"	"uk pop"
## [183]	"indietronica"	"dance"
## [185]	"chillstep"	"modern indie folk"
## [187]	"chanson"	"bubblegum dance"
## [189]	"death metal"	"vocal trance"
## [191]	"mellow"	"german dance"
## [193]	"indie rockism"	"melodic dubstep"
## [195]	"swedish singer-songwriter"	"persian pop"
## [197]	"ccm"	"meme"
## [199]	"funk carioca"	"trap queen"
## [201]	"norwegian pop"	"swiss pop"

## [203]	"slowed and reverb"	"east coast hip hop"
## [205]	"meme rap"	"indiecoustica"
## [207]	"chamber psych"	"g funk"
## [209]	"gauze pop"	"k-rap"
## [211]	"new wave pop"	"finnish alternative rock"
## [213]	"calming instrumental"	"nashville indie"
## [215]	"australian electropop"	"chill house"
## [217]	"pixel"	"ann arbor indie"
## [219]	"bhojpuri pop"	"reggae fusion"
## [221]	"folktronica"	"teen pop"
## [223]	"otacore"	"native american"
## [225]	"alabama rap"	"belgian dance"
## [227]	"latin hip hop"	"industrial pop"
## [229]	"swedish pop"	"german pop"
## [231]	"cleveland indie"	"slap house"
## [233]	"jazz cover"	"wave"
## [235]	"funk metal"	"new england americana"
## [237]	"indie viet"	"bc underground hip hop"
## [239]	"virginia indie"	"chicago house"
## [241]	"newfoundland indie"	"austin rock"
## [243]	"canadian old school hip hop"	"epicore"
## [245]	"british soul"	"eurobeat"
## [247]	"latin pop"	"australian indie"
## [249]	"chiptune"	"melodic metalcore"
## [251]	"viral rap"	"belgian pop"
## [253]	"dreamo"	"shimmer psych"
## [255]	"dutch indie"	"pop dance"
## [257]	"a cappella"	"garage rock revival"
## [259]	"pakistani hip hop"	"covertronica"
## [261]	"australian r&b"	"hopebeat"
## [263]	"canadian celtic"	"lo-fi product"
## [265]	"british soundtrack"	"italian library music"
## [267]	"australian psych"	"new romantic"
## [269]	"reggaeton"	"compositional ambient"
## [271]	"pop folk"	"classic progressive house"
## [273]	"bow pop"	"indonesian singer-songwriter"
## [275]	"austindie"	"indie soul"
## [277]	"christian alternative rock"	"adult standards"
## [279]	"chinese electropop"	"memphis hip hop"
## [281]	"brazilian edm"	"acoustic opm"
## [283]	"armenian hip hop"	"j-idol"
## [285]	"children's folk"	"detroit indie"
## [287]	"lgbtq+ hip hop"	"country"
## [289]	"celtic rock"	"scorecore"
## [291]	"la indie"	"electro"
## [293]	"anime latino"	"j-acoustic"
## [295]	"swedish electropop"	"canadian singer-songwriter"
## [297]	"uk alternative hip hop"	"classic country pop"
## [299]	"escape room"	"speedrun"
## [301]	"arab trap"	"uk hip hop"
## [303]	"cantopop"	"classic swedish pop"
## [305]	"dark plugg"	"glitch"
## [307]	"tempe indie"	"anthem worship"
## [309]	"sleaze rock"	"funk"

## [311]	"arkansas country"	"chinese idol pop"
## [313]	"french shoegaze"	"swiss indie"
## [315]	"weirdcore"	"liquid funk"
## [317]	"odia pop"	"noise pop"
## [319]	"blues"	"oxford indie"
## [321]	"jazz rap"	"soul jazz"
## [323]	"pinoy hip hop"	"bhajan"
## [325]	"gujarati pop"	"j-ambient"
## [327]	"hare krishna"	"modern bollywood"
## [329]	"erhu"	"fingerstyle"
## [331]	"christian lo-fi"	"musica indigena latinoamericana"
## [333]	"disco house"	"modern folk rock"
## [335]	"filter house"	"hypnagogic pop"
## [337]	"german pop rock"	"atmospheric dnb"
## [339]	"dmv rap"	"irish singer-songwriter"
## [341]	"nightrun"	"korean electropop"
## [343]	"arab electronic"	"dark clubbing"
## [345]	"glam metal"	"korean pop"
## [347]	"classic soul"	"pop quebecois"
## [349]	"belgian indie"	"alternative americana"
## [351]	"asian american hip hop"	"phonk brasileiro"
## [353]	"nashville singer-songwriter"	"chill baile"
## [355]	"hi-nrg"	"black americana"
## [357]	"french psychedelic"	"british alternative rock"
## [359]	"japanese piano"	"russian drill"
## [361]	"melbourne bounce international"	"indie emo"
## [363]	"cali rap"	"chennai indie"
## [365]	"french indie pop"	"electro-pop francais"
## [367]	"future rock"	"cinematic dubstep"
## [369]	"lithuanian electronic"	"punjabi hip hop"
## [371]	"diva house"	"english indie rock"
## [373]	"ambient lo-fi"	"indonesian lo-fi pop"
## [375]	"j-pop boy group"	"soundtrack"
## [377]	"persian electronic"	"christian rock"
## [379]	"boy pop"	"wonky"
## [381]	"barbadian pop"	"girl group"
## [383]	"ambient worship"	"singaporean singer-songwriter"
## [385]	"ballet class"	"florida drill"
## [387]	"trip hop"	"canadian latin"
## [389]	"g-house"	"telugu indie"
## [391]	"lilith"	"rap rock"
## [393]	"malaysian pop"	"brazilian bass"
## [395]	"cincinnati indie"	"nz hip hop"
## [397]	"south african pop"	"australian hip hop"
## [399]	"neon pop punk"	"manitoba indie"
## [401]	"classic bhangra"	"abstract"
## [403]	"hmong pop"	"city pop"
## [405]	"kazakh pop"	"cedm"
## [407]	"freeform hardcore"	"deep tropical house"
## [409]	"contemporary r&b"	"norwegian house"
## [411]	"danish electronic"	"grunge"
## [413]	"belgian rock"	"ethereal wave"
## [415]	"cumbia"	"dark pop"
## [417]	"cyberpunk"	"musica portuguesa contemporanea"

## [419] "classic uk pop"	"plugg"
## [421] "anime piano"	"nz pop"
## [423] "dance rock"	"chicago indie"
## [425] "modern dream pop"	"american modern classical"
## [427] "gambian hip hop"	"tech house"
## [429] "pluggnb"	"hawaiian hip hop"
## [431] "hungarian classical performance"	"argentine ambient"
## [433] "gangster rap"	"metallic hardcore"
## [435] "british modern classical"	"brighton indie"
## [437] "danish electropop"	"chinese classical performance"
## [439] "australian singer-songwriter"	"pakistani electronic"
## [441] "christian hip hop"	"toronto indie"
## [443] "lo-fi rap"	"japanese old school hip hop"
## [445] "melodipop"	"new jersey indie"
## [447] "k-pop girl group"	"scottish indie"
## [449] "permanent wave"	"abstract hip hop"
## [451] "electroclash"	"hawaiian"
## [453] "game mood"	"nyc rap"
## [455] "j-pop girl group"	"assamese pop"
## [457] "australian alternative pop"	

Inference: This code standardizes the genre column using the mapping defined in `genre_mapping`. The genres are recoded into broader categories, and the final unique values are verified.